**JP2.4** EXPANDING THE VARIATIONAL METHODS IN THE LAPS MOISTURE ANALYSIS

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## 1. INTRODUCTION

The Local Analysis and Prediction System (LAPS) analyzes three-dimensional moisture and other state variables each hour (or less) over a high resolution relocatable domain. LAPS analyses have been used to initialize local-scale, high-resolution models such as the Colorado State University's Regional Atmospheric Modeling System (RAMS) model and NCAR's MM5 (mesoscale model, version 5) on a routine basis as a means to utilize local data in the forecast model. LAPS has been integrated into the Advanced Weather Information Processing System (AWIPS) as part of the National Weather Service (NWS) modernization. Research to expand LAPS capabilities is one avenue toward providing advanced technologies and new innovations to the operational forecaster.

This paper describes work in progress and the next step toward advancing the variational technique in the LAPS moisture analysis. To date, the variational step has been used only with GOES sounder radiances. Other moisture variables were analyzed separately and either merged with that variational result or with the background field prior to the variational step (Birkenheuer 2000, 1999). This change will enable the use of more data in the variational framework. The solution strategy allows different data sources to be represented by different terms in the minimized functional. The functional can be automatically adjusted to match the datasets present. More important, this approach accommodates nonlinear functionals.

### 1.1 *Brief History of LAPS*

Under development since 1990, LAPS combines nationally disseminated data with local data for real-time objective analyses of all data available to the local weather forecast office. LAPS analyses are of suitable quality to initialize local-scale forecast models. Such models can address specific problems of a small forecast domain with greater detail than can be achieved with nationally disseminated model guidance (Snook et al. 1998).

The LAPS system is routinely tested with new data sources and innovative improvements, using more "conventional" data, which have potential for national dissemination.

During the 1980s FSL conducted forecast exercises to test its workstation prototypes. Forecasters were burdened with the impossible task of reviewing all the incoming data made possible through new technologies, while producing timely forecasts. It became obvious that local data needed to be objectively analyzed in conjunction with nationally disseminated data. Conceived as a resolution to this challenge, LAPS was designed to analyze all local data in real time on an affordable computer workstation and use its own output fields to initialize local-scale forecast models. So far LAPS has been interfaced with RAMS and MM5, but it can function with any weather prediction model. A more detailed review of LAPS is available in McGinley et al. (1991).

LAPS integrates all state-of-the-art data as they become routinely available to a field forecast office. Advanced data include Doppler reflectivity and velocity fields, satellite observations including GOES infrared (IR) image data in AWIPS format, wind profiler data, automated aircraft reports, and dual-channel ground-based radiometer data. New data sources included here are GOES-derived layer precipitable water data (GVAP), and Global Positioning System (GPS) data.

## 2. LAPS MOISTURE ANALYSIS

The specific humidity (SH) module is one of 17 LAPS algorithms that span everything from data preparation and quality control (QC) to actual analysis. In addition to state variables, LAPS also produces highly specific analyses of special interest, such as aircraft icing threat and relative humidity, both with respect to mixed and liquid phases.

### 2.1 *Background Setup*

Like most analysis systems, LAPS needs a starting field, which it later modifies by adding information from other datasets. This background or first-guess field for the test discussed here is FSL's Mesoscale Analysis and Prediction System (MAPS) analysis. Updated each hour, MAPS is the development model of the operational Rapid Update Cycle (RUC-2) at the National Center for Environmental Prediction (NCEP).

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The background model moisture data are interpolated to the denser LAPS grid and reconciled with the LAPS temperature analysis to avoid supersaturation.

### 2.2 *Boundary Layer Moisture*

The boundary layer moisture module utilizes surface humidity and mixes this into the calculated boundary layer by augmenting the moisture in the low levels of the 3-D grid. In the new system, the variational adjustments are allowed to modify the low-level moisture values, a change from the earlier algorithm.

### 2.3 *GVAP and GPS Pre-analysis*

The GVAP and GPS fields are individually preanalyzed prior to the variational step. This is done to specify data at all grid points. The preanalysis consists of a simple nearest grid point assignment of the observation, and a smoothed interpolated field between observation locations. In addition to the three GVAP fields (one for each sigma layer) and the one GPS field, each field has a corresponding weighting function. The spatial weight controls the horizontal influence of the data field at grid points near the one that represents the observation. This includes the spatial influence of observations and other error factors (i.e., limb effects for microwave data, a possible future consideration). In addition, data latency (temporal considerations) can be set up to modify data source influence in the variational step in this same function.

### 2.4 *The Expanded Variational Adjustment*

The variational adjustment using GOES radiances (Birkenheuer 1999) is being expanded to include GVAP layer precipitable water (over the column water previously analyzed), GPS total column water, and cloud information in one step. The cloud information is made available from the LAPS cloud analysis (Albers et al. 1996). The cloud analysis utilizes aircraft and surface reports, in addition to GOES visible and infrared satellite image data,and describes cloud vertical extent and horizontal distribution. In this newly revised variational approach, the cloud analysis is allowed to influence utilization of other data, specifically IR radiances.

### 2.5 *Cloud Saturation*

As a safeguard to assure consistency, a final check is made to the field to make sure that moisture is saturated in 100% cloudy areas with respect to the applicable water phase.

### 2.6 *Quality Control*

The final step in the SH algorithm is quality control. Each moisture value is compared to the LAPS analyzed temperature, and if supersaturated, it is reported and reduced to saturation. Typically, supersaturation rarely occurs.

## 3. DATA SOURCES

### 3.1 *GVAP Data*

GVAP data were obtained from the University of Wisconsin - Madison in real time on a daily basis (Menzel et al. 1998). The new variational scheme scales the appropriate parts of the LAPS moisture column to fit each of the three layers provided by GVAP data. The prior LAPS system only utilized total column GVAP water vapor data. The GVAP layers (defined as surface to 0.9 sigma, 0.9 to 0.7 sigma, and 0.7 to 0.3 sigma) are converted to a pressure coordinate system as part of the GVAP preanalysis. GVAP data have a nominal latency of 2 h at the current time.

### 3.2 *GPS Data*

GPS data are acquired from derived total column water vapor from signal delay (Wolfe et al., 2000). These data are real-time with a characteristic latency of 20 min. GPS data are immune from cloud effects, and therefore can be used where clouds are present. This capability is incorporated in the new functional of the variational analysis.

### 3.3 *Cloud Data*

Cloud data are obtained from the LAPS cloud analysis, which relies on satellite image data in addition to Doppler radar, ACARS, surface-based observations of sky conditions, and pilot reports. These data define clear fields of view for the variational adjustment, help saturate the atmosphere in cloudy regions, and influence the moisture analysis in partly cloudy regions.

## 4. VARIATIONAL FORMALISM

The mathematical formalism of the variational procedure is presented in equation 1. The advantage of this approach is that it offers a robust method for operational application and can accommodate nonlinear terms.

$$
\begin{aligned}
J = {} & S_{SAT} \sum_{k=1}^{7} \frac{GT(g_i)[R(t, cq, o_3)_i - R_i^o]^2}{E_{SAT}^2 L_{SAT}} + \sum_{i=1}^{N} \frac{(1-c_i)^2}{E_{BACK}^2} \\
& + S_{GPS} \frac{(\sum_{i=1}^{N} c_i q_i - Q^{GPS})^2}{E_{GPS}^2 L_{GPS}} \\
& + S_{GVAP} \sum_{j=1}^{3} \frac{G(g)(\sum_{i=1}^{N} P_{ji}(c_i q_i) - Q_j^{GVAP})^2}{E_{GVAP_j}^2 L_{GVAP}} + S_{CLD} \sum_{i=1}^{N} \frac{g_i [c_i q_i - q_s(t_i)]^2}{E_{CLD}^2 L_{CLD}}
\end{aligned}
\qquad (1)
$$

Each term in (1) is modified by the variable *S*, which is a switch (with the exception of the background term which is always on). Thereby, the terms can be used or not used depending on whether or not data are available or if clouds are present. Furthermore, a user can easily add terms for new data sets by simply creating a new term. Here the variables are as follows:

- $C_i$ the coefficient vector applied to $q$ to adjust the moisture field. Ideally this would have the same dimensions as $q$ has levels, but may be reduced depending on computer horsepower. Adjustment of this parameter is in essence the variational fit to the solution, i.e., $c_i q$ becomes the adjusted $q$ field. The adjustment coefficient is a scalar with a lower limit of 0 (never negative). A value of 1 indicates no change to the background. Because of this, the system will only work with a quantity such as temperature or humidity that uses absolute units. For example, using this approach to analyze temperature in degrees F will fail.
- $q$ the specific humidity profile at one LAPS grid point
- $R$ the forward-modeled radiance or radiance observation with the superscript $o$.
- $i$ index for the LAPS vertical (vector dimension of $q$), with a current maximum of 40 (accommodating the climatological stratospheric layers needed for the forward radiance model).
- $k$ the index indicating the satellite sounder or imager channel used.
- $Q^{GPS}$ the total precipitable water measurement from GPS.
- $E$ the error function (squared quantity) that describes the observation or background error, subscripted by observation type.
- $L$ spatial weighting term subscripted by observation type. This weights the smoothed (preanalyzed) field value by its proximity to the observation and reflects the horizontal influences of the measurement. Each data source has an associated gridded field of spatial-weighting terms characterizing its proximity to the observation and its spatial representation.
- $P$ the function to convert from pressure to sigma coordinates
- $Q^{GVAP}$ the GOES vapor total precipitable water layer data. The layers are defined in sigma coordinates and vary grid point to grid point.
- $j$ the index of the GVAP layer, with a current maximum of 3 (1 is lowest, 3 is highest).
- *Cld* cloud function designating cloudy regions in the vertical, with dimensions of $q$.
- $J$ the functional to be minimized.
- $t$ is the temperature profile (LAPS) at the same location as $q$.
- $S$ logical switch for the observation type to be present or not. Each term in the functional can be easily included or excluded depending on the presence of the data source. Also new data sources can be added by including new terms.
- $q_s(t)$ saturated $q$ as a function of temperature.
- $g$ cloud fraction indicator as a function of level.
- $G$ a function of $g$ such that it indicates cloud in the column. For radiance measurements, this has the advantage of disabling IR terms including GVAP. Finally, the GPS term would be unaffected by clouds in principle since the data source can deliver data in cloudy areas. However, the analysis needs to probably give more credence to the cloud field since it is vital the cloud field complements the moisture field ensuring that two fields don't conflict. $G$ can be a linear function of cloud such that it might serve to help define partly cloudy regions by allowing a smooth gradient from total through partly cloudy to clear air.
- $GT$ is a similar function to $G$, but it may be nonlinear and can match the satellite radiometer's field of view.

## 5. SOLUTION METHODOLOGY

The minimization of (1) is accomplished using the same methods as the prior moisture analysis. The Powell method (Brent 1973) employs a multidirectional search to seek out a solution. Typically two to five calls of the algorithm are required to solve the function. Each call to the numeric method involves 25 or so functional calls. Although more efficient methods are available, this technique has worked reliably to date. Model adjoints are not required for this technique.

## 6. EXAMPLE

A qualitative example of the new analysis is shown in Figs. 1 and 2. Figure 1a, shows a midlevel comparison (600-hPa relative humidity plot) of the former analysis with the newer adaptation of the variational method (Fig. 1b). Similarly, Figs. 2a and 2b show a high-level example at 400 hPa from the same time. Note that the cloud field is denoted as a white area, contours are at 10% RH intervals. The newer variational approach appears to capture more humidity

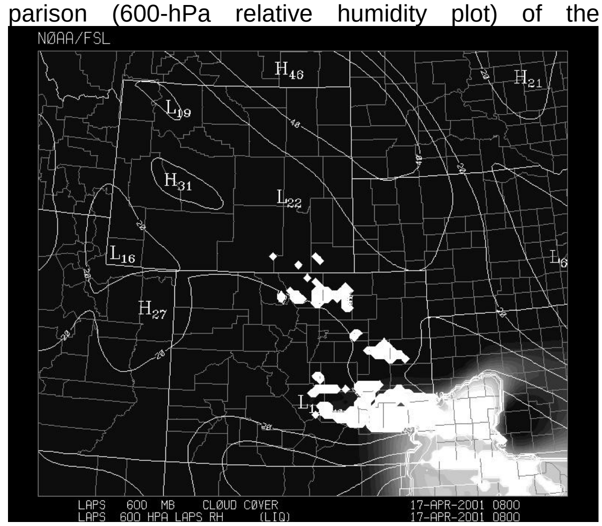


**Fig. 1a. The older analysis of the 600 hPa RH (contours at 10% intervals) showing analyzed cloud (grayscale) over the LAPS Regional Observing Cooperative (ROC) domain (17 April 2001).**

structure away from the cloud. Furthermore, the gradient about the cloud appears more gradual

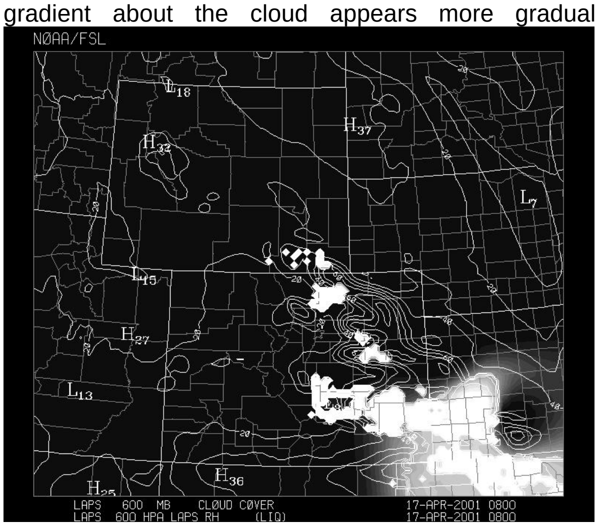


**Fig. 1b Same as Fig. 1a with the newer variational method using clouds and GVAP data.**

and perhaps is more realistic. More validation is required to establish that the new method is rendering a more accurate analysis.

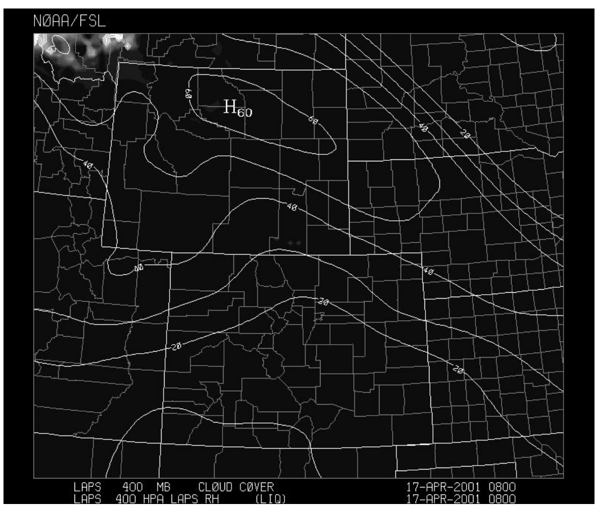


**Fig. 2a Older analysis of 400-hPa RH for the same time as in Fig. 1.**

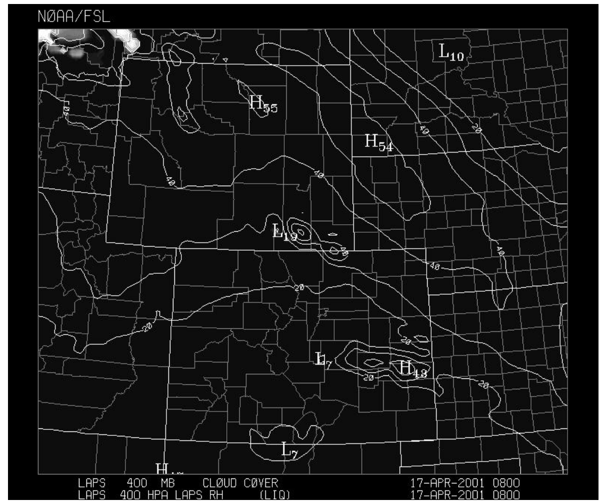


**Fig. 2b Similar to Fig. 1b except at 400 hPa.**

## 7. SUMMARY

The new functional solution is now being tested with broader focus on the run times and feasibility of real-time operation. These aspects of the algorithm look promising, even for AWIPS-type resources. Error functions are currently approximated and will require refinement. For this case GPS data were not used since they remain under development.

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